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Climatic Conditions and Productivity: An Impact Evaluation in Pre-industrial England*

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Abstract

In this paper, we bridge economic data and climatic time series to assess the vulnerability of a pre-industrial economy to changes in climatic conditions. We propose an economic model to extract a measure of total productivity from English data (real wages and land rents) in the pre-industrial period. This measure of total productivity is then related to temperatures and precipitations. We find that lower (respectively higher) precipitations (resp. temperatures) enhance productivity. Further, temperatures also have non-linear effects on productivity: large temperature variations lower productivity. We perform counterfactual exercises and quantify the effects of large increases in temperatures on productivity, GDP and welfare.

Keywords: Climatic conditions, TFP shocks, real wages, real rents.
JEL Classification: C22, N13, O41, O47, Q54.

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1 Introduction

In this paper, we use historical data in England before the Industrial Revolution to assess its economic vulnerability to changes in climatic conditions (temperatures and precipitations). We use real wages and real agricultural rents time series from 1669 to 1800 to obtain a measure of productivity, and investigate empirically the sensitivity of productivity to temperatures and precipitations. This relation is exploited to derive an impact evaluation of an exogenous rise in temperature on economic activity. The results might serve as an informative benchmark for currently under-developed economies that might suffer from the upcoming climatic, even though these economies evolve in a different economic and climatic envrionment than pre-industrial England.

First, we propose a simple growth model where economic activity depends on structural factors and exogenous shocks. The model establishes simple and testable relations between the prices of production factors (wages and rents) and the main driver of the economy (productivity). The use of such models to describe the dynamics of pre-industrial economies is very frequent in the literature (see for instance Aguiar and Gopinath [2007] or Neumeyer and Perri [2005]). Second, we make use of the wages and rents process to extract an empirical measure of productivity from the data. Third, we investigate the impact of two climatic factors (temperatures and precipitations) on productivity.

Our focus is on pre-industrial England, as this economy shared some important characteristics with currently emerging or under-developed economies: a large agricultural sector, slow technological innovations, few ways to diversify individual risks, political instability, major impact of diseases and climatic calamities. We find that precipitations affect productivity negatively while temperatures play a positive role. However, our econometric specification allows for non-linear effects in addition to these effects. While non-linear (quadratic) effects of precipitations are statistically non-significant, temperatures have non-linear effects on productivity. Hence, large temperature variations (positive or negative) lower productivity. From a quantitative perspective, our simulations indicate that a permanent two-degree rise in temperatures in pre-industrial England would have lowered the level of productivity by more than 27%, and production by more than 30%. Most currently under-developed economies (sub-saharan economies for instance) face different climatic conditions and could certainly adapt climatic change better than pre-industrial England would have. Further, the contemporaneous climatic conditions are not directly comparable to and CO^2 concentrations are much larger nowadays, with likely effects on the relation between climatic conditions and productivity. However, we argue that our results bring some useful information about the potential effects of climatic change in currently under-developed economies, even though they might be seen as an upper bound.

Our paper relates to the emerging and growing literature that using historical dataset study the potential effect of global warming on long-run economic growth. Empirical evidence remains very limited. A part of the literature explores empirically the effects of year-to-year fluctuations in temperature on economic outcomes (see Dell, Jones and Olken [2012], Burgess, Deschenes, Donaldson and Greenstone [2011], Deschenes and Greenstone [2007], [2012]). The authors point out that the effects of short-term temperature fluctuations are likely to be different than the effects of long-term temperature change. An another part of the literature provides empirical evidence on the long term effect of gradual temperature changes on economic growth (see Waldinger [2014]). Examining the long term effect of gradual temperature change on economic growth during the Little Ice Age, from 1500 to 1750, evidence indicates that decreased temperatures led to shortened growing periods and more frequent harvest failure in this period. Using historical wheat prices, the author shows that temperatures affected economic growth through its effect on agricultural productivity.

The paper is organized as follows. Section 2 contains a brief description of the data. Section 3 presents our main assumptions and the econometric results. Section 4 present simulations results at regular business cycle frequency and the results of our counterfactual experiments.

2 Data

We collect three different types of data. The first one is an annual sequence of English real wages starting in 1264.[1]

The second source of data comes from Gregory Clark's website.[2] We gather all the 4.983 rents of the Charity Commission Land Rents data set from 1502 to 1800. The full data set extends to 1912 but we concentrate on the pre-industrial period. The oldest record goes back to 1394, but there is no data from this date on to 1502. We use the estimated annual rental value of land in pounds (including land tax if paid by the tenant). Although the data set contains many details regarding the type of land – its usage, its owner – very few observations are directly comparable. We thus simply divide the estimated rent by the total surface to obtain a proxy of the rental rate. An immediate consequence however is a considerable amount of unobserved heterogeneity. To mitigate this heterogeneity, we only consider observations for which we have a sufficiently large amount of data (namely 10 per year), which leaves us with 132 different observations, an annual time series starting in 1669 and ending in 1800. Finally, we deflate these rents by the Retail Price Index, provided by measuringworth.org, to obtain a sequence of real rents.

The last source of data concerns climatic conditions.[3] The data set includes the annual mean temperatures for an area around London (average of 4 grid points which is around 5000 km^2) and the annual cumulated precipitations from 1500 to 2000.

Table 1 and Figure 1 give a brief description of the data.

Two interesting features of the wages and rents time series can be stressed. First, they do not display any clear trend. Second, annual variations are quite large. Both features are strikingly different from what is currently observed in developed countries. In those countries, rents and wages are much more stable and wages display a clear upward trend. The trend in wages follows the upward trend in real GDP and is one of the growth stylized facts. Private and public insurance systems may account for the

[1]This exceptionally long sequence is available at http://www.measuringworth.org.

[2]We used the sources documented in http://www.econ.ucdavis.edu/faculty/gclark/papers/rentweb.txt. For the land rents data, we only consider the England South East region since it corresponds to the geographical place where the climatic investigations have been conducted.

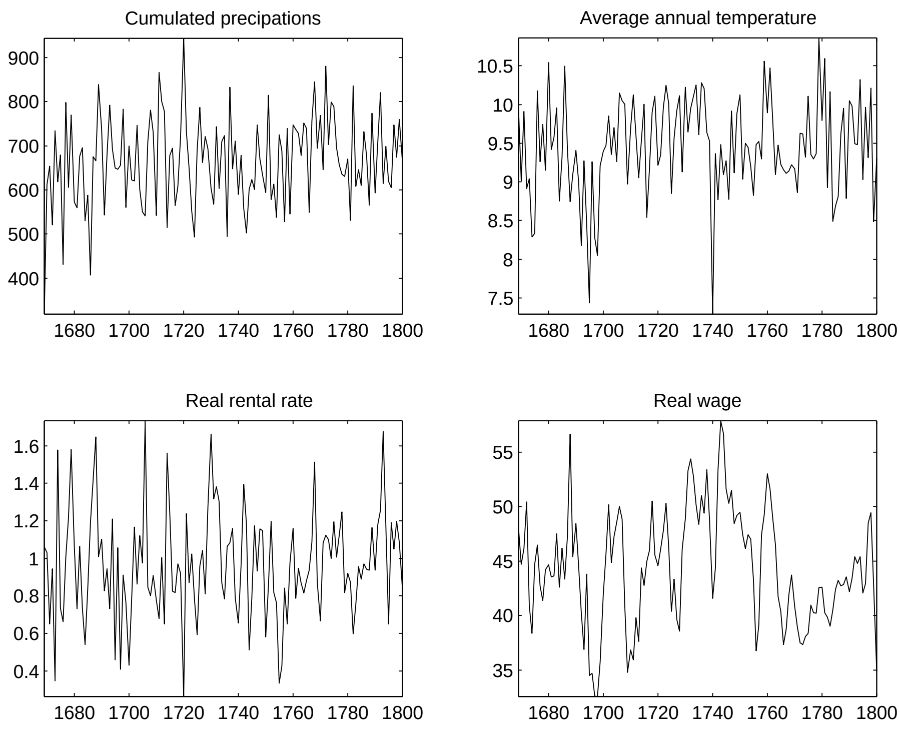
[3]We would like to thank Juerg Luterbacher for providing this data set.

Table 1: Descriptive Statistics

Series	Min	Q_1	Med.	Q_3	Max	Aver.	Std. Err.	Kurt.
Wages	32.58	40.75	44.36	48.38	57.9	44.39	5.22	-0.25
Rents (in %)	0.26	0.79	0.95	1.16	1.73	0.97	0.28	0.45
Precipitations	318.93	601.15	672.11	734.45	943.99	664.87	101.13	0.50
Temperatures	7.29	9.11	9.44	9.94	10.86	9.45	0.62	0.9

Note: Wages are given as their equivalent in the £ of 2010. Rents are percent per annum. Precipitations are annual cumulated in millimeters. Temperatures are given in Celsius degrees.

Figure 1: Raw time series



low variability. Several centuries ago, growth was much lower and insurance systems were much less efficient or did not exist at all. From this point of view, our data show that pre-industrial England resembled the currently poorest areas of the World.[4]

In addition, Table 2 shows that the correlations between economic and climatic variations are statistically significant.

Table 2: Correlation coefficients

	Temperatures	Precipitations
Wages	0.30 (0.00)	−0.23 (0.01)
Rents	0.17 (0.05)	−0.10 (0.24)

Note: Numbers below coefficients are p-values of the F-test for statistical significance.

In particular, temperatures and economic time series tend to move together while precipitations and economic time series move in opposite directions. However, this first-pass description of the data cannot be used directly for our purpose since non-linear phenomena may play an important role.[5] Hence, potential relations, linear or not, between climatic conditions and factor prices (wages and rents) must be further investigated. Finally, the reaction of economic agents to good or bad states of the economy implies the reallocation of resources over time, with consequence on rents, wages, or savings. This implies dynamic relationships that cannot be captured by the –contemporaneous– correlations displayed in Table 2. In the next section, we propose a model based on agents decisions to capture these interactions and to guide us in our impact evaluation.

3 Fluctuations, factor prices and productivity

Our analysis is based on the Hercowitz and Sampson [1991] model, also used in Collard [1999], which is a variation of the usual Solow growth model. The main advantages of using this model are that it can be solved exactly, without relying on approximation

[4] Notice that these wage and rent time series are real prices.

[5] For instance, it may be noted wages averaged over ten years show a 5% difference before and after the worst flooding episode, which occurred in 1760.

methods, and that it provides testable micro-founded relations between productivity levels and key macroeconomic aggregates (factor prices, GDP, consumption, welfare). A possible limitation of the model is however that, with only one production sector, it neglects the potential sectoral reallocations of labor and capital that might occur after large shocks on productivity induced by changes in climatic factors. After presenting some of the key features of the model, we present a method to extract a measure of total factor productivity, that is confronted with climatic data to infer the impact of climatic variations on productivity. A detailed account and analytical derivation of the model is provided in Appendix A, while the main text contains only the most relevant features.

3.1 Model

We assume that the representative agent maximizes a time-separable utility function

$$E_0 \left[\sum_{t=0}^{+\infty} \beta^t \log(C_t) - \chi \log(1 - N_t) \right], \tag{1}$$

with respect to consumption (C_t) and labor (N_t) paths subject to the following constraints

$$C_t + I_t = W_t N_t + R_t K_{t-1} + \pi_t, \tag{2}$$

$$K_t = A_K K_{t-1}^{\delta} I_t^{1-\delta}. \tag{3}$$

Equation (2) is the budget constraint, where W_t and R_t respectively denote the real wage and the real rate, and π_t is the representative firms' profit. In the model, we consider land as a stock of capital. Although modeling an agricultural economy usually requires some specificities (production depends on land and labor, but also on animals and seeds), we argue that assimilating capital and land is a fair approximation of a production process combining labor and capital, at least at the aggregate level. First, when the land is not cultivated, it remains idle and therefore "depreciates", in the sense that it does not contribute to production anymore. If it is to be used again after remaining unused, fertilization requires a lot of resources and time, that can be considered as an investment. Second, at the aggregate level, new land can be cultivated when needed. This increase in the surface of cultivated land also requires economic resources (deforestation, time, fertilization), which can also be considered as an investment. Third, according to the data, the total surface of cultivated land rose from 10 millions of acres in 1600 to 11.5 millions of acres in 1800, suggesting that land is an adjustable factor at the aggregate level (see Wrigley [2010], Table 3). Hence, from now on, we assimilate capital and land, and the real rate coincides with the real rental rate.

Concerning Equation (3), it captures the law of motion of the "capital stock" K_t. This equation which is a variation of the usual linear case first proposed by Lucas and Prescott [1971] (see also Hercowitz and Sampson [1991]). The parameter $0 < \delta < 1$ may be interpreted as a quality of installed capital (or the fertility of land).[6] The main advantage of this formulation of capital accumulation is that it allows to derive a closed-form solution of the model, something highly appreciable when trying to capture the effects of large shocks. Allowing to track the dynamics of the model without relying on linear approximations around the steady state also comes at some cost. This assumption is indeed well-known to produce a constant saving rate and results in constant hours worked when the model is driven by productivity shocks only.[7] However, both implications are not unreasonable within the context of pre-industrial England. First, engines of savings where quite limited. For most workers savings where basically zero, as most of the population was at the subsistence level (see Galor [2005]). For farmers, savings basically consisted in storing a constant fraction of their production (seeds) for the next year. Second, movements in the labor force were mainly related to movements of total population, as captured by Malthusian models (again, see Galor [2005]). Hence, participation in the labor market and endogenous movements in labor supply (movements that were unrelated to changes in the population) were very limited.

The profits of the representative firm are $\pi_t = Y_t - W_t N_t - R_t K_{t-1}$ where Y_t is the production level. We model the production process as $Y_t = A_t K_{t-1}^{\alpha} N_t^{1-\alpha}$ where A_t is the Total Factor Productivity level (TFP hereafter) affected by random shocks and

[6]This formulation may also account for adjustment costs, the capital stock at time t being a concave function of investment I_t.

[7]When driven by additional shocks like public spending shocks, the model would produce a time-varying saving rate and variable hours worked (see Auray, Eyquem and Jouneau-Sion [2014]).

K_{t-1} is the installed capital available for production at time t. It is labeled with one lag since it depends on decisions and random events up to date $t-1$. As explained in Appendix A, a possible solution to the optimization problem is given by $Y_t = SI_t$ where $S = \alpha\beta(1-\delta)/(1-\delta\beta)$. Using the convention $x_t = \log(X_t)$ for every almost surely positive sequence X_t, the law of motion for (the logarithm of) the capital stock is

$$k_t = a_K + (1-\delta)s + \rho k_{t-1} + (1-\delta)a_t, \tag{4}$$

where $\rho = \delta + (1-\delta)\alpha$.

If we assume that the random shocks A_t are such that $a_t = log(A_t)$ admits an ARMA(p,q) representation, Equation (4) shows that the installed capital stock admits an ARMA(p+1,q) representation. As $\rho < 1$ since both α, δ belong to $]0,1[$, k_t converges to a stationary random process whenever a_t is stationary.

3.2 Productivity shocks extraction

Our ultimate objective is to quantify the impact of climatic conditions on productivity and aggregate macroeconomic variables. Our first step is thus to use our model to extract the (unobserved) productivity process a_t. Our model allows us to derive the TFP process as an explicit function of the bivariate observable stochastic process r_t, w_t, *i.e.* wages and rents. The relation arises from the model itself. Indeed, agents are assumed to react optimally to unobservable shocks, and these reactions affect observable variables, such as prices. This extraction strategy solely relies on wages and rents and not on the climatic time series.

As explained in Appendix A, the model implies the following system of equations

$$r_t = \log(\alpha) + y_t - k_{t-1}, \tag{5}$$

$$w_t = \log(1-\alpha) + y_t - n, \tag{6}$$

$$y_t = \alpha k_{t-1} + a_t + (1-\alpha)n, \tag{7}$$

where we have used the fact that hours worked are constant in equilibrium, *i.e.* $n_t = n$. Equations (5) and (6) derive from the maximization of private profits. Equation (7) is the production function expressed in logs, where we use the fact that n_t is a constant term that may be computed explicitly. Substituting Equation (5) in (7) gives

$$y_t = \alpha(\log(\alpha) + y_t - r_t) + a_t + (1-\alpha)n, \tag{8}$$

and using Equation (6) we get

$$(1-\alpha)(w_t - \log(1-\alpha)) + \alpha(r_t - \log(\alpha)) = a_t. \tag{9}$$

3.3 Statistical inference

Before we can extract the TFP process using Equation (9), we need to estimate the parameter α. Direct regression of w_t on r_t (or the other way around) would lead to biased estimates, since r_t and a_t are correlated. We rely on the Generalized Method of Moments (GMM hereafter). Assume a_t is a strong ARMA(1,q) process

$$a_t = (1-\rho_a)a_\infty + \rho_a a_{t-1} + \epsilon_t + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}, \tag{10}$$

where $(\epsilon_t)_{t>0}$ is a strong white noise. The process $(\epsilon_t)_{t>0}$ is the genuine – unobserved – sequence of exogenous shocks. In particular, the random variable ϵ_t is independent from – observed – quantities w_s, r_s if $s < t$ since agents are not able to forecast perfectly these shocks.

Hence, $(1-\alpha)(w_t - \rho_a w_{t-1}) + \alpha(r_t - \rho_a r_{t-1})$ and $\epsilon_t + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}$ differ only by some constant term. It implies that the following moment equations

$$Cov[(1-\alpha)(w_t - \rho_a w_{t-1}) + \alpha(r_t - \rho_a r_{t-1}); w_{t-j}] = 0, \tag{11}$$

$$Cov[(1-\alpha)(w_t - \rho_a w_{t-1}) + \alpha(r_t - \rho_a r_{t-1}); r_{t-j}] = 0, \tag{12}$$

must hold for all $j > q$. These moment conditions may be used to estimate (α, ρ_a). The statistical device amounts to compute the solution of the following program

$$\min_{\hat{\alpha}', \hat{\rho_a}} v^{\mathrm{T}}(\hat{\alpha}, \hat{\rho_a}) \Omega v(\hat{\alpha}', \hat{\rho_a}), \tag{13}$$

where Ω is a positive definite matrix of size $2h \geq 2$ and

$$v(\hat{\alpha}', \hat{\rho_a}) = \begin{pmatrix} Cov[(1-\alpha)(w_t - \rho_a w_{t-1}) + \alpha(r_t - \rho_a r_{t-1}); w_{t-q-1}] \\ \ldots \\ Cov[(1-\alpha)(w_t - \rho_a w_{t-1}) + \alpha(r_t - \rho_a r_{t-1}); w_{t-q-h}] \\ Cov[(1-\alpha)(w_t - \rho_a w_{t-1}) + \alpha(r_t - \rho_a r_{t-1}); r_{t-q-1}] \\ \ldots \\ Cov[(1-\alpha)(w_t - \rho_a w_{t-1}) + \alpha(r_t - \rho_a r_{t-1}); r_{t-q-h}] \end{pmatrix}. \tag{14}$$

An asymptotically optimal choice of Ω then provides GMM estimates of our parameters. If $2h > 2$, we have more constraints than we strictly need to perform the estimation. Hausman [1978] shows that these extra constraints may be used to test whether data reject the model or not. Using the GMM method with $q = 2$ and $h = 6$ we get the results reported in Table 3.[8]

Table 3: GMM estimates

	coef.	std. err.	p. value
α	0.1124	0.0053	0.0000
ρ_a	0.5978	0.0054	0.0000
J-stat			0.0904

The coefficient α is significant and positive. The above estimate is consistent with a low return on capital, with respect to estimates derived using data on developed economies. It is also consistent with a high share of labor income in total income. In addition, the autocorrelation parameter of the TFP process is somehow lower than those usually estimated for currently developed economies. Finally the model appears well specified, as the p-value of the Hausman specification test is $0.0904 > 0.05$, which means that the model is not rejected by the data at the 95% confidence level.

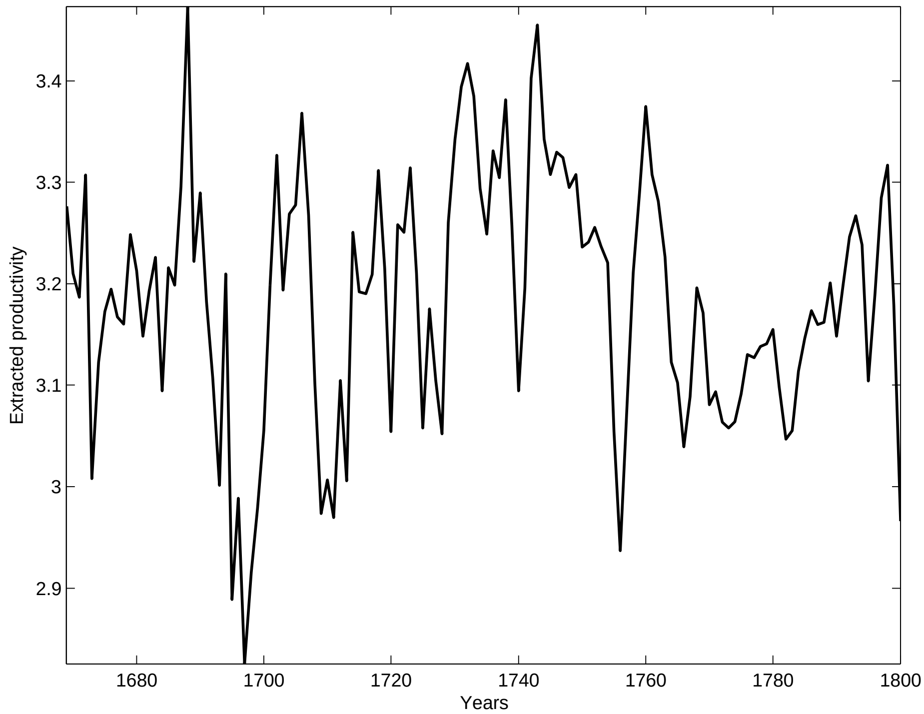
3.4 Impact evaluation

The estimate of α can now be plug in Equation (9) to extract the TFP process, $\hat{a}_t$, reported in Figure 2.

We are now able to evaluate how climatic conditions affect productivity over this period of time in pre-industrial England. Remember that the extracted path of $\hat{a}_t$ did *not* make any use of the climatic time series. In particular, if economic variables and climatic time series were independent, $\hat{a}_t$ should be independent of changes in climatic conditions, as it was derived as a function of real prices only.

[8]Estimation proceeds in two steps. The first step consists in estimating $(\hat{\alpha}', \hat{\rho_a})$ using the identity matrix. The second step uses an optimal weighting matrix Ω that is the inverse of the long-run variance-covariance matrix of moment conditions build using the first-step estimate of $(\hat{\alpha}', \hat{\rho_a})$. The weighting matrix is corrected from its dynamic heteroscedasticity using a Bartlett Kernel to insure that final (second-step) estimates are unbiased.

Figure 2: Extracted productivity process ($\hat{a}_t$)



We estimate an ARMAX(1,1) model for $\hat{a}_t$ where the X vector of additional explanatory variables includes functions of temperature and precipitations. Our largest potential specification is the following:

$$\hat{a}_t = \phi_0 + \phi_1 \hat{a}_{t-1} + \gamma_1 \text{Prec}_t + \gamma_2 \text{Prec}_t^2 + \beta_1 \text{Temp}_t + \beta_2 \text{Temp}_t^2 + \xi_t + \theta_1 \xi_{t-1}, \qquad (15)$$

where variables are taken in level, except for precipitations, that are expressed in deviation from their means. The variable Temp_t^2 is the square of Temp_t, and Prec_t^2 is defined accordingly. Our specification includes potential non-linear effects from climatic conditions as extreme events may have different effects on productivity than regular small variations of climatic conditions. We report the results for the different specifications in Table 4.

Model (1) is a simple ARMA(1,1) where the X vector does not play any role. The result tells us that the AR(1) coefficient is significant but not the MA(1) coefficient. The AR(1) coefficient is in line with our GMM-estimated value of ρ_a. Results for models (2) and (3) show that precipitations significantly affect productivity but the

Table 4: ARMAX model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ϕ_0	1.0996^a (0.0258)	1.1217^a (0.0238)	1.1560^a (0.0179)	0.7990^a (0.1534)	-1.6872^b (0.6696)	-2.2541^a (0.2477)	-2.1739^a (0.5756)
ϕ_1	0.6542^a (0.0112)	0.6475^a (0.0106)	0.6377^a (0.0105)	0.6345^a (0.0174)	0.6354^a (0.2073)	0.6391^a (0.0996)	0.6123^a (0.2040)
Precipitations	–	-0.1473^a (0.0539)	-0.1448^a (0.0539)	–	–	-0.1601^a (0.0516)	-0.1575^a (0.0522)
$(\text{Precipitations})^2$	–	–	-0.1525 (0.2719)	–	–	–	–
Temperature	–	–	–	0.0385^a (0.0107)	0.5769^a (0.0195)	0.7017^a (0.0130)	0.7039^a (0.0211)
$(\text{Temperature})^2$	–	–	–	–	-0.0290^a (0.0012)	-0.0360^a (0.0005)	-0.0362^a (0.0032)
θ_1	-0.0012 (0.0552)	-0.0165 (0.0543)	0.0002 (0.0553)	-0.0489 (0.0555)	-0.0315 (0.0463)	-0.0621^c (0.0353)	–
R^2	0.4207	0.4515	0.4527	0.4570	0.4776	0.5119	0.5108
$Adj-R^2$	0.4071	0.4343	0.4310	0.4399	0.4569	0.4885	0.4914
Loglikelihood	127.97	131.56	131.69	132.22	134.76	139.22	137.54
AIC	−249.93	−255.12	−253.38	−256.44	−259.52	−266.44	−265.08
BIC	−241.28	−243.59	−238.96	−244.91	−245.10	−249.14	−250.67

Note: Standard errors in parentheses, with a, b, and c respectively denoting significance at the 99%, 95% and 90% confidence levels.

non-linear effect is not statistically significant. Higher-than-average precipitations actually reduce productivity. While this might seem surprising, this is in line with our initial correlation matrix (see Table 1), and can be explained (among other things) by losses in seeds when precipitations occur immediately after seeding. Results for models (4) and (5) indicate that temperatures significantly affect productivity at the 99% level both linearly and with a non-linear effect. The linear effect is positive while the non-linear effect is negative. This means that a small rise in temperatures has positive effects on productivity while larger changes (positive or negative) lead productivity to fall. Results for model (6) show that the level effect of precipitations on productivity, when combined with linear and non-linear effects of temperatures, further improves the fit of the model with the data. This specification returns a weakly significant MA(1) coefficient. Finally, model (7) is simply model (6) where the MA(1) coefficient has been forced to zero. AIC and BIC criteria produce opposite decisions concerning the best fit between model (6) and model (7), but owing to the larger adjusted R-squared for model (7), we keep this parsimonious specification for our simulation exercises.

Alternative specifications were also tested. An interaction term combining precipitations and temperatures (not reported) was included but turned out to be non-significant, and adjusted R-squared was lower. A Threshold Autoregressive (TAR) model where temperatures are the threshold variable was also estimated (see Appendix B). Even though this model identified a significant threshold on temperatures at 9.915 degrees (temperatures above the 73^{th} percentile) with opposite effects (positive below the threshold, negative above) on productivity, the model produced a substantially lower R-squared of 0.4086. In addition, coefficients in the regime of high temperatures were not statistically significant. In both cases, we chose not to consider those specifications further.

4 Simulations and counterfactual experiments

We now use model (7) to perform two types of exercises. The first one is a simulation based exercise where we assess the ability of the model to match business cycle features of the observed economic times series. The second experiment consists in assessing the counterfactual impact on productivity of a two-degree rise above the average temperature.[9]

4.1 Business cycle moments

Simulations of the path of wages and rents require some additional information about the value of δ. Indeed, the way the dynamics of wages depends on TFP can be described explicitly, as the logarithm of real wages is an ARMA(1,1) transformation of the TFP process:

$$w_t = (\log(1-\alpha) - \alpha n)(1-\delta)(1-\alpha) + (\delta + (1-\delta)\alpha)w_{t-1} + a_t - \delta a_{t-1} \qquad (16)$$

Hence, using our extracted path of productivity and based on Equation (16), we derive GMM estimates of δ and the constant term. We obtain $\hat{\delta} = 0.2545$.[10] Feeding the model with a productivity path with characteristics (standard deviation of innovations and autocorrelation) that are similar to the path of productivity predicted by model

[9] A two-degree rise corresponds to the lower bound of the rise induced in something like 100 years by the actual change in climatic conditions according to the IPCC.

[10] Again we remark that this figure is low compared to contemporary estimates.

(7) above, we report key business cycle statistics predicted by the model and compare them to those of observed data.[11]

Table 5: Business cycle statistics

	Data		Model	
	Wages	Rents	Wages	Rents
Standard deviation	0.12	0.33	0.12	0.11
Autocorrelation	0.72	0.12	0.66	0.06
Correlation with wages	–	0.28	–	0.46
Correlation with productivity	0.77	0.14	0.99	0.52

The fit with observed moments is satisfactory for the volatility and persistence of wages, and acceptable for the correlation between wages and rents. Concerning rents, the fit is less satisfactory in that the volatility and persistence are too low. Similarly, correlations of factor prices and productivity implied by the model are too high with respect to the data. Qualitatively however, the model performs reasonably well in matching business cycle moments.

4.2 Counterfactual experiments

We now conduct three counterfactual experiments: a one-time two-degree rise in temperatures, an immediate permanent two-degree rise in temperatures, and a gradual 0.02-degree rise each year, inducing temperatures to be two degrees above the sample average after 100 years. As explained in Appendix A, because our model is quite simple, output and welfare correspond exactly to real wages (up to some constant terms), so the log-deviations from the steady state are identical. Further, once the path of wages and productivity are known, using Equation (9) gives the path of real rents. Finally, Equation (5) gives the path of the capital stock. The effects of a one-time two-degree shock are reported in Figure 3 while Figure 4 contrasts the effects of a permanent (gradual or immediate) two-degree rise.

The model predicts that a temporary increase in temperatures would induce a 11% decrease in TFP. Accordingly, the corresponding fall in wages, output and welfare

[11] Because observed data are stationary, simulated and observed data were not filtered.

Figure 3: Impact on TFP of a one-time two-degree rise

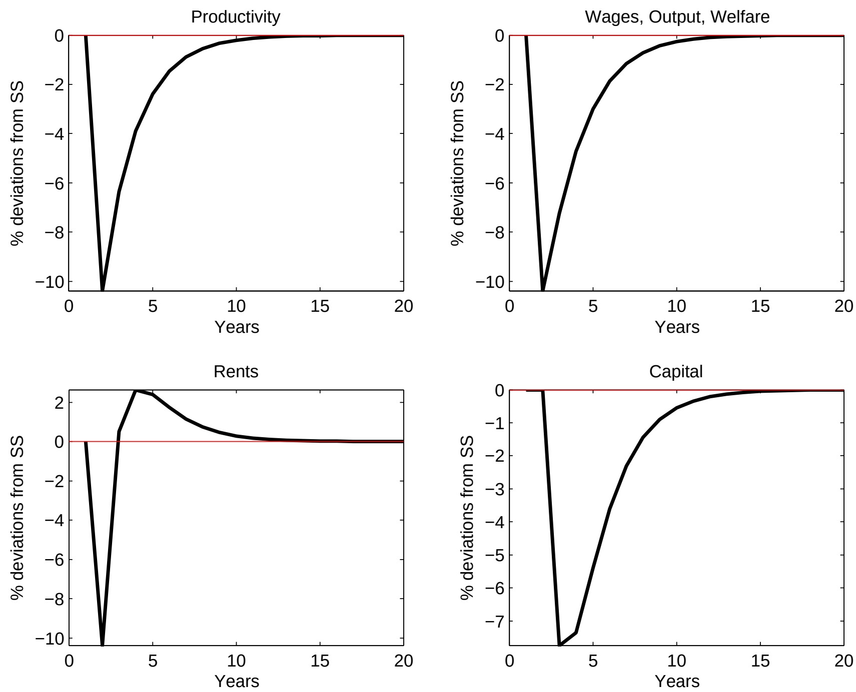
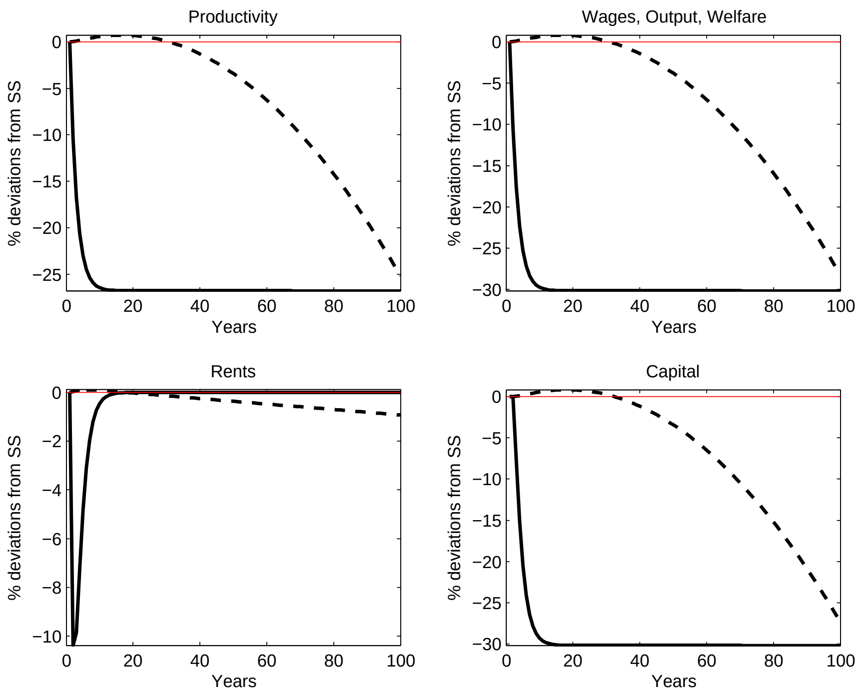


Figure 4: Impact on TFP of a permanent two-degree rise.
Solid: gradual. Dotted: immediate



would be 11% and the capital stock would fall by 8%. While this figure is very large, a two-degree rise represents a 21% increase in temperatures, which is also very large: a two-degree rise above the mean (11.45 degrees) is above the maximal temperature observed in our sample (10.86). In addition, the dynamics implied by the shock exhibit relatively little persistence, as productivity and relevant macroeconomic aggregate are back to the steady state after 10 years.[12]

With a permanent rise, the effect on productivity is different whether the rise is immediate or gradual, due to the non-linearity of the ARMAX model. With an immediate rise, the effects on productivity are large, around 27% and the fall in output, wages and welfare reaches 30%. The economy stabilizes to its new steady state after 10 years, consistently with the moderate autocorrelation parameter estimated from our extracted productivity path. With a gradual rise, the effects reveal the non-linearity identified in the data. As temperature starts to rise moderately, productivity, wages, output, wages, rents and capital rise as well. When the rise in temperatures is large enough for the negative (non-linear) effects of the rise to overturn the positive (linear) effects, productivity starts to plunge. Hundred years after temperatures started to rise, productivity ends up reaching the level predicted after 10 years with an immediate shock. However, the transition path is characterized by a non-linear fall in most relevant macroeconomic aggregates, and a continuous fall in the real rate. The magnitude of the effects of a gradual change in temperatures 100 years after climatic conditions start to change is very much comparable to the magnitude induced by an immediate change, but transition paths differ markedly.

5 Conclusion

In this paper, we quantify the impact of temperatures and precipitations in England over the period 1669-1800. Using a standard growth model and historical data on real wages and real rents, we extract the variations of productivity that could be due to the reallocation of labor and land. The remaining source of variations is then related to climatic factors. Large changes in temperatures affect TFP negatively in

[12]Recall however that our model tends to underestimate autocorrelation.

this pre-industrial economy. A temporary two-degree rise in temperatures induces a 11% decrease in TFP with similar effects on output, wages and welfare. A permanent two-degree increase in temperatures leads to a 27% decrease in TFP, and to a 30% fall in wages, output and welfare. These results could serve as a useful benchmark to assess the vulnerability of currently under-developed economies to upcoming climatic changes.

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A Details of the model

Let $E_t[X_s]$ be the expectation of the value of the random process $(X_r)_{r\geq 0}$ at date s conditionally on the available information set at date t. Households maximize their lifetime welfare at time t

$$E_t\left[\sum_{s>t}\beta^s \log(C_s) + \chi \log(L_s)\right], 0 < \beta < 1, \tag{A.1}$$

subject to their budget constraint

$$C_t + S_t = W_t N_t + R_t K_t + \pi_t, \tag{A.2}$$

where W_t is the real wage, $N_t = 1 - L_t$ is the level of hours worked, S_t is the saving flow, and $\pi_t = Y_t - W_t N_t - R_t K_t$ is the profit realized by the unit of production.

Two additional constraints are taken into account for maximization, namely the production function

$$Y_t = A_t K_{t-1}^{\alpha} N_t^{1-\alpha}, 0 < \alpha < 1, \tag{A.3}$$

and the modified law of accumulation of capital

$$K_t = A_K K_{t-1}^{\delta} I_t^{1-\delta}. \tag{A.4}$$

The transformed maximization program writes

$$\max_{C_{t\geq 0}, N_{t\geq 0}} E_0\left[\sum_{t>0}\beta^s \log(C_s) + \chi \log(1 - N_s)\right] \tag{A.5}$$

$$K_t = A_K K_{t-1}^{\delta}\left(A_t K_{t-1}^{\alpha} N_t^{\alpha} - C_t\right)^{1-\delta}\ \forall t > 0 \tag{A.6}$$

First Order Conditions are

$$\frac{1}{C_t} = \frac{\lambda_t(1-\delta)K_t}{I_t}, \tag{A.7}$$

$$\frac{\chi N_t}{1 - N_t} = \frac{\lambda_t(1-\delta)K_t}{I_t}(1-\alpha)Y_t, \tag{A.8}$$

$$\lambda_t K_t = \beta E_t\left[\lambda_{t+1}K_{t+1}\left(\delta + \alpha(1-\delta)\frac{Y_{t+1}}{I_{t+1}}\right)\right], \tag{A.9}$$

$$K_t = A_K K_{t-1}^{\delta}\left(A_t K_{t-1}^{\alpha} N_t^{\alpha} - C_t\right)^{1-\delta}, \tag{A.10}$$

A particular solution to the above system such that $S_t = SY_t$, and $\lambda_t K_t = X$ can be derived. Using these assumptions, the above system becomes

$$S = \frac{X(1-\delta)}{1+X(1-\delta)}, \tag{A.11}$$

$$\frac{\chi N_t}{1-N_t} = \frac{X(1-\delta)(1-\alpha)}{S}, \tag{A.12}$$

$$1 = \beta E_t \left[\delta + (1-\alpha)(1-\delta)\frac{1}{S}\right], \tag{A.13}$$

$$K_t = A_K K_{t-1}^{\delta} \left(A_t S N^{1-\alpha}\right)^{1-\delta}, \tag{A.14}$$

Equation (A.13) provides S as a function of preference, production and capital accumulation parameters. Using Equation (A.11), we also get X as a function of these parameters. Equation (A.12) shows that labor is a fixed proportion of the available time, hence $N_t = N$. Equation (A.14) is Equation (4) in the main body of the text. Finally, maximization of the individual profit of the firm implies that real factor prices must equal their respective marginal productivity, which gives Equations (5) and (6) in the main text. In our setup, the link between welfare and reals wages derives from the following argument. The utility function is

$$U(C_s, L_s) = \log(C_s)+\chi\log(L_s) = \log((1-S)Y_t)+\chi\log(N) = \log((1-S)+\chi\log(N)+y_t. \tag{A.15}$$

Hence the (logarithm of the) total output equal the welfare up to a constant. As $w_t = \log(1-\alpha) + y_t + n$, both y_t and/or w_t may be used as a measure of welfare.

The dynamic link between welfare (or, as we just claimed, the logarithm of real wages) and TFP may then be derived explicitly. We have

$$k_t = a_k + (1-\delta)s + \delta k_{t-1} + (1-\delta)y_t, \tag{A.16}$$

$$y_t = \alpha k_{t-1} + a_t + (1-\alpha)n, \tag{A.17}$$

$$w_t = \log(1-\alpha) + y_t - n. \tag{A.18}$$

Using the production function to substitute for y_t, we get

$$\begin{aligned} k_t &= a_k + (1-\delta)s + \delta k_{t-1} + (1-\delta)(\alpha k_{t-1} + a_t + (1-\alpha)n) \\ &= a_k + (1-\delta)(s + (1-\alpha)n + a_t) + (\delta + (1-\delta)\alpha k_{t-1}, \end{aligned} \tag{A.19}$$

$$w_t = \log(1-\alpha) + \alpha k_{t-1} + a_t - \alpha n. \tag{A.20}$$

As $\alpha > 0$ both equations combine to yield

$$w_{t+1} = (\log(1-\alpha) - \alpha n)(1-\delta)(1-\alpha) + (\delta + (1-\delta)\alpha)w_t + a_{t+1} - \delta a_t. \quad \text{(A.21)}$$

B Estimation results of the TAR model

The specification of the threshold model is the following

$$\hat{a}_t = \phi_0^a + \phi_1^a \hat{a}_{t-1} + \gamma_1^a \text{Prec}_t + \beta_1^a \text{Temp}_t + \xi_t, for \text{Temp}_t > tn \quad \text{(B.1)}$$

$$\hat{a}_t = \phi_0^b + \phi_1^b \hat{a}_{t-1} + \gamma_1^b \text{Prec}_t + \beta_1^b \text{Temp}_t + \xi_t, for \text{Temp}_t \leq tn \quad \text{(B.2)}$$

where tn is the temperature threshold that alters the characteristics of the relationship between climatic conditions and productivity. Table 6 below reports the results.[13]

Table 6: Estimation results of the TAR model

Threshold (tn)	9.915^a (0.0577)	
	Temp $\leq tn$	Temp $> tn$
ϕ_0	0.7167^a (0.2782)	3.4395^a (0.6650)
ϕ_1	0.5619^a (0.0728)	0.03810 (0.0334)
Precipitations	-0.1680^a (0.0619)	-0.1793 (0.1253)
Temperature	0.0737^a (0.0214)	-0.0342 (0.0682)
R^2	0.4660	0.0751
Joint R^2	0.4086	

Note: Standard errors in parentheses, with a, b, and c respectively denoting significance at the 99%, 95% and 90% confidence levels

[13] The model was estimated using Bruce Hansen's Matlab code, available at *http : //www.ssc.wisc.edu/ bhansen/progs/progs_threshold.html*